Playing Fast and Frugal with Stock Market Forecasts[§]

Markus Glaser * Zwetelina Iliewa **

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Abstract

We conduct a natural field experiment with professional forecasters and document a significant bias in their stock market expectations resulting from prevalence of intuitive judgment as opposed to deliberate forecasting methods. There is a significant difference between professionals' expectations when they are asked to forecast stock price levels or returns directly - two questions intensively used and considered interchangeable in real-world surveys. The difference constitutes a significant violation of the procedure invariance assumption of normative decision theory. According to our evidence the reason for professionals to rely too often on their flawed gut feeling lies in an extreme confidence, a characteristic of intuitive responses, instead of lack of motivation or cognitive busyness. The exact wording of the question also seems to influence the reliance on intuition - fast, confident and evidently flawed responses are often provided whenever subjects forecast price levels as opposed to returns.

Keywords: natural field experiment, professional forecasters, judgmental forecasting, framing effect, intuition

JEL Classification: G1, C93

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* Markus Glaser is from the Institute for Capital Markets and Corporate Finance, Ludwig-Maximilians-Universität Munich, Schackstr. 4, 80539 Munich, e-mail: glaser@bwl.lmu.de

** Corresponding author: Zwetelina Iliewa, Centre for European Economic Research (ZEW) Mannheim, L7.1, 68161 Mannheim and the Institute for Capital Markets and Corporate Finance, Ludwig-Maximilians-Universität Munich, e-mail: iliewa@zew.de

1 Introduction

Consider following thought experiment: Ask your investment advisor where the stock market is headed a month from now. Divide the answer by a constant, say the current level of the stock market index. Pose the question again, but this time ask directly about the ratio. Would you expect any fundamental difference between the responses of your investment advisor other than a little bit of rounding? According to our evidence you should.

In this paper we focus on the stock market expectations of professionals and provide evidence on a significant violation of the procedure invariance assumption of normative decision theory (framing effect). We examine the difference in stock market expectations when the exact elicitation form is varied - asking subjects to forecast future stock price levels versus asking them to forecast stock returns. We are interested in the difference between these particular forms of elicitation, because they are used interchangeably in regular real-world surveys (see, e.g., Duke/CFO Magazine Business Outlook Survey for return forecasts; see, e.g., Livingston Survey of the Federal Reserve Bank of Philadelphia for a price level forecasts). Experimental evidence by Glaser, Langer, Reynders, and Weber (2007) challenges the information content of such real-world surveys by showing that the resulting expectations are predictably affected by the way they are elicited. Whether the framing effect is limited to survey-based expectations alone or to expectations which underly investment decisions determines the scope of the impact the framing effect might have on financial markets - from the validity of survey-based sentiment indicators and financial advisory to biases in investment decisions and the development of financial market variables. It remains an empirical question whether real-world decision makers are susceptible to the framing effect in their forecasts and decisions and, if so, when and why. In this study we address these questions by conducting a natural field experiment with 188 financial market professionals from leading financial companies (banks, insurance companies, large corporates) in Germany.

The main results of our study can be summarized as follows: Firstly, we provide evidence that the framing effect is economically and statistically significant in the forecasts of stock market professionals. Secondly, we show that the framing effect is driven by intuitive thinking as measured by both self-reported measures and reaction time. Hence, judgmental forecasting, which makes use of fast and frugal but in financial markets not necessarily helpful heuristics, is particularly relevant even for the real-world forecasts of professionals. Thirdly, our results suggest that the reason for professionals to rely on their intuition is the extreme confidence that comes with it, not low motivation or low cognitive capacities. We also draw attention to the elicitation form which is strongly preferred by professionals, namely price levels. According to our evidence it is exactly the domain of price levels which drives the framing effect and in which participants are more prone to rely on their flawed intuition.

De Martino, Kumaran, Seymour, and Dolan (2006) provide neurobiological evidence on the more widely studied manifestation of the framing effect - valence framing, the difference in revealed preferences when information is presented in the domain of gains or losses. In a discussion of this study, Kahneman and Frederick (2006) ascribe the occurrence of the valence framing effect to intuition, better yet, its basic inability to disregard superficial features such as the exact representation of information or the exact wording of the question. Several recent experimental and empirical studies evidence an impact of intuitive thinking on biases in financial market expectations and investment decisions of retail investors and students. Grinblatt, Keloharju, and Linnainmaa (2011) and Grinblatt, Keloharju, and Linnainmaa (2012) analyze the impact of IQ, a proxy for high tendency to trust one's gut feeling (see e.g., Stanovich and West, 2002), on the investment decisions of private investors and find that a low IQ score results in a higher susceptibility to behavioral biases and inferior portfolio allocation. A conceptually similar proxy is used by Kumar and Korniotis (2013) who analyze the impact of cognitive abilities on investment performance. The authors thereby approximate cognitive abilities with correlated demographic factors. Kempf, Merkle, and Niessen-Ruenzi (2012) link affect to stock market return expectations in an experimental setting and provide evidence on biased risk-return expectations resulting from intuitive judgment. According to the experimental evidence by Glaser and Walther (2013) subjects make inferior investment decisions in times their intuition is in play. To the best of our knowledge this is the first study to use data on financial market professionals to evidence a link between prevalence of intuition and a bias in expectation formation.

2 Data

2.1 The Panel of the ZEW Financial Market Survey

The ZEW Financial Market Survey is a monthly survey conducted since December 1991 among roughly 350 financial market professionals. The panel of participants covers a heterogeneous sample of financial market practitioners: active (e.g., portfolio managers) and passive (e.g., professional forecasters); sell-side, i.e. participants from large German companies, and buy-side participants, i.e. investors and investment advisors. Participants are initially selected by ZEW and invited to participate in the panel for their occupation as financial market professionals at leading financial institutions (banks, insurance companies) and large industrial companies in Germany. According to their occupation, participants are categorized as follows: treasurer (26.25%), economist or asset researcher (20%), portfolio manager (13.75%), advisor (8.13%), trader (7.5%), and other (e.g., corporate executives, wealth manager etc.). The participants are almost exclusively male (only 6 female participants). Within the scope of the survey questionnaire participants are generally asked about their mid-term forecasts (6 months ahead) on macroeconomic variables, interest rates, international stock market indices and foreign exchange. Furthermore, the survey questionnaire always contains a Special Questions section on diverse financial market topics and participants are used to responding to it whenever the topic is in their area of expertise.

The participants are not provided with any monetary incentives. However, all participants regularly and timely receive the press releases containing the survey results of the most recent wave. Timely and detailed information on the survey results is evidently valuable to the participants because of the comparably high overall market attention to scheduled releases of two indicators calculated from the survey responses - ”ZEW Economic Sentiments” for Germany and ”ZEW Current Situation” for Germany. Bloomberg ranks scheduled release indicators based on their relevance as approximated by the number of release alert subscriptions of Bloomberg users. As of October 2012 the Bloomberg relevance indicators for ZEW Economic Sentiments and ZEW Current Situation were with 98.24 points and

94.74 points comparable to the relevance index of the European Central Bank Interest Rates Announcements (97.67 points) and higher than the relevance indicators for macroeconomic announcements such as the German consumer price index (75.44 points) and the unemployment rate in Germany (84.21 points). As the results are evaluated and published strictly anonymously there are no incentives for strategic response behavior such as rational herding. There are no mandatory questions or any other restrictions of the response behavior. Moreover, participants are encouraged to respond strictly according to their area of expertise.

In September 2012 we collected background information on the methods used by experiment participants when conducting short-term DAX forecasts - the main focus of our experiment. An overview of the results is included in Figure 6 in the Appendix. Technical analysis is by far the most intensively used forecasting tool - 64.75% of the participants indicate that it is of great importance for their short-term forecasts. This result is in line with recent evidence by Menkhoff (2010) on the wide usage of technical analysis of fund managers in Germany, especially for an investment horizon of several weeks. Another study by Hoffmann and Shefrin (2011) surveys the methods used by online investors and shows that technical analysis is the second most preferred method after intuition. The consistency with both studies indicates a high representativeness of the ZEW panel of financial market professionals. Further factors which play a role for the short-term DAX forecasts are experience, fundamental analysis and intuition with respectively 43.44%, 30.58% and 22.13% of the participants ranking them as highly important. In contrast, the majority of participants consider econometric models and simulations of low importance for their short-term DAX forecasts.

2.2 Experimental Design

In the period from September 2012 until June 2013 we conducted a quarterly repeated field experiment with the professional stock market forecasters from the ZEW Financial Market Survey. Within the scope of the field experiment we asked the online participants to forecast the German stock market performance index DAX one month ahead (point forecast) and to provide their subjective 90% confidence intervals. The experimental questions were included as a quarterly repeated part of the regular survey; this is why no additional incentives for participation were necessary, other than the non-monetary incentives to participate in the ZEW panel (see Section 2.1). The questions were included at the end of the survey questionnaire within a flexible part called Special Questions. Prior to the first wave of the field experiment the subjects were randomly divided into two equally sized groups - a return group and a level group (randomized between-subject design). The participants did not receive any indication that an experiment was being conducted and they were unlikely to expect it because experiments had never been conducted within the scope of the ZEW Financial Market Survey before. The experimental design is as close to a real-world forecasting task as can be and can be categorized as a natural field experiment in the terms of Harrison and List (2004). Our experiment thus combines the advantages of laboratory experiments (randomization) and natural experiments (realism).

The exact wording of the questions for the level group and the return group are given as follows:

I expect the DAX in 1 month at ... points. With a probability of 90% the DAX will then lie between ... and ... points.

Within 1 month I expect a DAX return (monthly percentage change) of ... %. With a probability of 90% the DAX return will then lie between ... % and ... %.

In order to retain high ecological validity the questions for both groups are adopted from existing regular surveys. The questions for the level group are adopted from a regular question within the ZEW Financial Market Survey on mid-term DAX forecasts (6 months ahead), which has been a part of the survey since 2003 (see Deaves, Lüders, and Schröder, 2010). The exact wording of the questions for the return group is adopted from the Duke/CFO Magazine Business Outlook Survey (see Ben-David, Graham, and Harvey, 2012) and adjusted to the shorter forecasting horizon of our experiment. We include a definition of returns in brackets, "monthly percentage change", in order to specify that non-annualized returns are required. Feedback to a beta version of our questionnaire indicated that financial market professionals usually understand "returns" as "annualized returns" unless stated otherwise. The questions on subjective confidence intervals in the return group and the level group are held comparable in spite of the deviation from the exact wording of Ben-David, Graham, and Harvey (2012) in order to avoid well-documented differences in the width of subjective confidence intervals resulting from the elicitation format (see e.g., Soll and Klayman, 2004).

[Insert Figure 1 about here]

In each wave the respondents had roughly two weeks to submit their response: 31.08.-17.09. (September 2012 wave), 26.11.-10.12. (December 2012 wave), 04.03.-18.03. (March 2013 wave) and 03.06.-17.06. (June 2013 wave). Overall, 188 professionals participated in the experiment with an average of 2.85 responses, which resulted in a total of 535 responses. As illustrated in Figure 1 the period covered an overall bullish market phase on the German stock market. The survey questionnaire does not contain any information on the German stock market or any other information sources. However, since we restrict the experiment to the online participants of the ZEW panel, it is plausible to assume that they have timely access to all publicly available information and are well informed about the current level of the assets they frequently track (including DAX).

The forecasts of the level group are converted into return forecasts using the DAX daily open on the day of the response (calculation method "daily open"). Whenever the response was submitted on a Saturday, Sunday or an official holiday the DAX daily close of the last working day prior to the day of the response is applied. Daily data on DAX is downloaded from Datastream. Since there is a clustering of responses before noon (50% of the responses are submitted before 12 o'clock), using the daily opening price as a proxy for the actual DAX level is connected to a rather small measurement error in most of the cases. Additionally, in order to account for a potential measurement error resulting from intraday trends, we have conducted robustness checks using the average between the DAX daily open and the DAX daily close on the day of the response (calculation method "daily avg").

We exclude responses for which the forecast lies outside the subjective 90% confidence interval (consistency check).

The participants have not received any feedback on their own DAX one-month forecasts. Furthermore, participants have not received any feedback on the aggregate responses to the experimental questions, as the results were not published in any form.

3 Framing Effect and Judgmental Forecasting Outside the Lab

The study by Glaser, Langer, Reynders, and Weber (2007) experimentally examines the particular framing effect in stock market expectations - asking subjects to forecast future stock price levels or asking them to forecast stock returns - and casts serious doubt on the information content of real-world surveys. The authors support their claim that the effect is more than an experimental artefact by demonstrating that the difference in the findings of academic studies on subjective stock market forecasts can be explained by the use of different questions. This is true for studies with students and professionals alike. The argument that finance professionals are not immune to judgmental biases altogether is proclaimed by a handful of studies: Northcraft and Neale (1987) document a significant use of the anchoring-and-adjustment heuristic by real estate experts; Roszkowski and Snelbecker (1990) provide evidence on valence framing effect in a study with financial planners. More recent studies even go one step further and alert that professionals may even be more susceptible to judgmental biases than students: Haigh and List (2005) show that traders on the Chicago Board of Trade exhibit higher myopic loss aversion than students; Gilad and Kliger (2008) demonstrate that investment advisors in large commercial banks and accountants in CPA firms are more prone to priming than students.

The opposite view is supported by Schoorman, Mayer, Douglas, and Hetrick (1994), who cast serious doubt on the real-world relevance of framing effects altogether. The authors argue that real-world relevant business decisions are connected to a large amount of available information and information evidently mitigates the valence framing effect, which they examine. Furthermore, in some environments and for some tasks framing effects are evidenced to diminish with the relevance of the task (see e.g., Schoorman, Mayer, Douglas, and Hetrick, 1994; McElroy and Seta, 2003), expertise in the task and statistical knowledge (see e.g., Bless, Betsch, and Franzen, 1998). These arguments would be particularly valid reasons not to expect any framing effect in professionals' forecasts if professionals could be assumed to be able to acquire actual skills and expertise in forecasting, and if they could generally be assumed to make use of statistical forecasting tools. However, there is evidence against both assumptions: firstly, psychological studies argue that the acquisition of expertise is impossible on financial markets altogether (Kahneman and Klein, 2009); secondly, the use of statistical methods by professionals should not be taken for granted, as evidently even they rely on inferior forecasting methods instead (see Menkhoff, 2010).

In a first step we therefore examine whether expectations of professional stock market forecasters are susceptible to the particular framing effect under study. We formulate following hypotheses:

`H1`: *Stock market expectations of professionals violate procedure invariance (prevalence of the framing effect).*

`H2`: *The framing effect diminishes in the presence of experience with the forecasting task and statistical knowledge.*

Violations to procedure invariance, such as the framing effect under study, are generally understudied. Particularly, the scarce existing literature does not provide any evidence on the role of intuition for the emergence of the particular framing effect. However, McElroy and Seta (2003) provide experimental evidence that the more intensively studied valence framing effect is determined by intuitive thinking. Furthermore, De Martino, Kumaran, Seymour, and Dolan (2006) provide neurobiological evidence that the valence framing effect is determined by emotional processes - a result which is interpreted by Kahneman and Frederick (2006) in terms of dual-process theory. The psychological literature on dual processing hypothesizes that judgments and decisions are generally a result of two systems of thoughts - a fast, effortless, automatic and emotional intuition, labeled System 1, and a slower and more effortful reasoning, labeled System 2 (see e.g., Kahneman, 2003; Stanovich and West, 2002). The way System 1 works is by subconsciously making use of fast and frugal heuristics. Glaser, Langer, Reynders, and Weber (2007) suggest a particular heuristic which explains the sign of the framing effect in their experiment - the representativeness heuristic. When asked to forecast stock market returns, participants tend to extrapolate recent trends (trend continuation). In contrast, when asked to forecast future price levels, expectations indicate anticipated mean-reversion. The use of the representativeness heuristic, as explained by Andreassen (1988), results in differences in subjective expectations arising from differences in the most representative value, the historical mean, of the historical prices and the historical returns respectively. It appears plausible that students use heuristics for their expectations in laboratory experiments with limited information and a relatively low relevance of the task. But is it plausible that professionals rely on heuristics, when heuristics yield flawed responses, and not on their presumably better judgment? A recent study by Hoffmann and Shefrin (2011) surveys private investors and documents that they admit to primarily using their own intuition when making investment decisions. Furthermore, Meyler and Rubene (2009) provide evidence on professional forecasters from the ECB Survey of Professionals Forecasters, who admit to using judgment more often than econometric or fundamental analysis when conducting macroeconomic forecasts. Furthermore, Northcraft and Neale (1987), Mussweiler and Schneller (2003) and Campbell and Sharpe (2009) provide evidence that the expectations of professionals are compatible with the use of heuristics.

In a second step we therefore test whether the fundamental difference between return and price level forecasts of professionals is driven by intuition and hence arises from the application of fast and frugal heuristics.

H3: *The tendency to suppress intuitive judgment diminishes the framing effect.*

In contrast, another strand of literature on questionnaire design alerts that framing effects may only be an apparent bias and rather results from fundamental differences in the information content of allegedly identical survey questions (see e.g., Bradburn, 1982; Bruine de Briun, Klaauw, and Topa, 2011). While in real-world surveys on stock market expectations the questions on future stock price levels and future stock returns are used interchangeably, there is no evidence that practitioners understand them the same way.

3.1 Are Professionals Prone to Framing?

In the following we test hypotheses `H1` and `H2`. In summary, our evidence suggests that professionals are prone to framing. The difference between their price level forecasts (converted in returns) and their one-month return forecasts is as large as 1.35% on average and thereby both economically and statistically significant. Against the predictions, the framing effect is larger in the group of participants experienced with short-term forecasts. Statistical knowledge appears to be a remedy against the framing effect. As predicted, the bias is small and insignificant in the group of participants with high statistical knowledge.

Our proxy for experience captures participants' experience with short-term forecasts as opposed to mid-term forecasts. The groups are divided according to self-reported evidence on subjects' usual forecasting horizons. A question on the usual forecasting horizon was included in the survey as a Special Question prior to the first wave of the field experiment, in March 2012. The distribution of the responses is displayed in the Appendix, Figure 7.

Statistical knowledge is approximated by the self-reported importance of econometric models for the conduction of the respondents' DAX forecasts. The data was collected within the scope of a Special Question in the survey. The information is available for both short-term forecasts (one-month ahead) and mid-term forecasts (six-months ahead). A minority of 6.61% of the participants consider econometric models highly important for short-term forecasts but overall 25.41% of the participants use statistical methods for short-term or mid-term forecasts. The statistical knowledge of an individual and the use of statistical tools for a particular task and in particular situations may diverge whenever forecasts have to be conducted rather quickly (e.g., for short forecasting horizons) and whenever the application of statistical tools is more effortful (e.g., for high-frequency data). As we are interested in the statistical knowledge of the participants, not the use of statistical tools for the particular task, we combine all available information on the use of statistical methods. For the purposes of our proxy we assume that participants with a high level of statistical knowledge ascribe greater importance to statistical tools for some of their forecasts (short-term, mid-term or both), participants with an average level of statistical knowledge ascribe average importance to statistical tools for at least some of their forecasts (short-term, mid-term or both) and participants with a low level of statistical knowledge do not use statistical tools for any of their forecasts.

Table 1 shows that the framing effect is significant, both economically and statistically, in expectations of professional forecasters. Asking professionals about the expected monthly return as opposed to the index level results in significantly more optimistic expectations.

[INSERT TABLE 1 ABOUT HERE]

We report coefficients from panel regressions and cluster-robust standard errors.[1] According to Table 1, regression 1, the average difference in optimism over all three waves is as high as 1.35 percentage points. A monthly expected return of 1.35 percent (17.5 percent in annualized terms) implies a strong investment recommendation on the part of the return group. Following the average forecast of the level group, in contrast, an investor would be advised to refrain from short-term investments in the DAX as such an investment is connected to an expected, albeit insignificant, loss. Given the overall positive trend during the four waves of our experiment, the evidence is consistent with an use of the representativeness heuristic as discussed by Glaser, Langer, Reynders, and Weber (2007). Figure 2 displays the cumulative distributions of the return expectations of the return group and the level group for each wave. In all four waves the cumulative distribution of the return group lies almost entirely underneath the cumulative distribution of the level group. Independent of the actual stochastic distribution of DAX returns we can conclude that the share of optimists in the return group is larger than in the level group, where optimism measures one's tendency to expect higher return than the actual mean of the return distribution.

[INSERT FIGURE 2 ABOUT HERE]

[1] We have also estimated mixed models with individual, wave and treatment random effects for all regressions included in the paper. All reported results are robust to the exact model specification.

Table 1, regression 5, displays the results on the impact of statistical knowledge on the scope of the framing effect. Participants are split into three groups according to their level of statistical knowledge - high (31 participants), medium (48 participants) and low (43 participants) statistical knowledge. Dummy coding is used for the group with a low level of statistical knowledge and the group with a medium level of statistical knowledge. Our results suggest that the scope of the framing effect is lower with advanced statistical knowledge and becomes insignificant with 0.76 percentage points in the group with a high level of statistical knowledge. The difference in the scope of the framing effect between the groups with low and high levels of statistical knowledge is economically significant (1.24 percentage points) but statistically insignificant at the significance level of 10%.

Table 1, regression 3, displays the results regarding the impact of experience on the scope of the framing effect. The participants are split into two groups according to their level of experience with the exact experimental task - experienced with short-term forecasts (49 participants, $D^{noexp} = 0$) and experienced with long-term forecasts (85 participants, $D^{noexp} = 1$). Experience with short-term forecasts does not mitigate but rather intensifies the framing effect. The scope of the framing effect in the group which is experienced with short-term forecasts is as high as 2.18 percentage points and significant at the 1% significance level.

All result are robust to alternative methods of calculation of return expectations from price level forecasts. The results for the alternative calculation method ("daily avg") are displayed in Table 1, columns (2), (4) and (6). The evidence has motivated further studies on the determinant of the framing effect as conducted in the following sections.

3.2 The Impact of Intuition on the Framing Effect

In the following we test hypothesis `H3` on the impact of intuitive thinking on the framing effect. We measure intuitive thinking firstly by self-reported measures and secondly by means of reaction times. In line with hypothesis `H3`, the framing effect in our sample is driven mainly by participants who put relatively high weight on their intuition and rely on it at least as much as on analytical mothods. The scope of the framing effect in this group of participants is namely more than three times higher than in the group of more analytical forecasters. Fast responses also exhibit significantly larger framing effect as compared to slow and better thought through responses, which is also in line with our hypothesis.

A. Self-reported Measures

In September 2012 we included a question on the factors which are important for the conduction of one's own forecasts. Among other things, participants were asked to rate the importance of intuition on a three-point Likert-scale with the categories "low", "medium", "high". We collected data from 123 of the participants in our experiment and the group sizes are given as follows: low importance (34 participants), medium importance (62 participants), high importance (27 participants). From this question we construct two alternative measures of intuitive thinking which capture the absolute importance of intuition and its relative importance as compared to analytical methods. The absolute importance of intuition reflects "Faith in Intuition" - the participants' tendency to trust their initial gut feeling in forecasting tasks (see Epstein, Pacini, Denes-Raj, and Heier, 1996, for a description and factor analysis of the short Rational-Experiential Inventory). Our measure of the relative importance of intuition is constructed analogously to the Intuitive-Analytical Score introduced by Sjöberg (2003). We use participants' responses to an exhaustive list of analytical factors - technical analysis, fundamental analysis, econometric models, simulations, inhouse forecasts and consensus forecast - and compare the most important one among them with the importance of intuition (within-subject, between-factor comparison). Based on the relative importance of intuition, participants are divided into three groups and the group sizes are given as follows: intuition is much less important than analytical methods (27 participants), intuition is less important than analytical methods (56 participants), intuition is of comparable importance or more important than analytical methods (39 participants).

Table 2 and Figure 3 show that the scope of the framing effect is largest in the group of intuitive forecasters as measured by both Faith-in-Intuition and Intuitive-Analytical-Score.

Asking participants with the highest Faith-in-Intuition to forecast returns instead of price levels results in more optimistic forecasts by 2.06 percentage points. We report coefficients from panel regressions and cluster-robust standard errors.

[Insert Table 2 about here]

[Insert Figure 3 about here]

In the group with medium Faith-in-Intuition, the scope of the framing effect is lower by 0.9 percentage points, in the group with low Faith-in-Intuition the effect is lower by 1.12 percentage points. The interaction terms are of high magnitude but are not statistically significant because of the comparably small group size of the participants with high Faith-in-Intuition. As can be seen from Table 2, regressions 3-4, the magnitudes of the interaction terms are higher according to the relative measure of intuitive thinking - the Intuitive-Analytical score - and are both economically and statistically significant at a significance level of 10%.

B. Reaction Time

Reaction times are generally used to distinguish between intuitive and deliberate approaches to decision-making (see e.g. Rubinstein, 2007). For our purposes we make use of the characteristic of intuition to provide fast and effortless responses and assume that short reaction times reflect intuitive responses whereas longer reaction times are more likely to reflect analytical responses. Reaction times have a great advantage against survey-based measures of intuition because they are not prone to any self-reporting biases.

In March we measured the time participants take to respond to the Special Questions section (reaction time). We measure the reaction time from the moment the participants receive the first question of the Special Questions section (including our experimental questions at its very beginning) until the moment the answers are submitted.[2] Some participants have returned to the previous parts of the questionnaire after entering the Special

[2] We have also measured the reaction time for the Special Questions in June 2013. However, the reaction time analysis based on the wave June 2013 did not reveal any significant pattern, because the scope

Questions section. These participants are excluded from the analysis, because their reaction time is biased upwards. For the same reason we also exclude participants who wrote an open-field comment before submitting their answers.

The experimental part of the Special Questions section in March 2013 contained the usual short-term DAX forecasts (point estimates and subjective confidence intervals). The remaining Special Questions addressed participants' estimates on the gold price, assessment of the fair value of both DAX and gold, an assessment of the correlation between DAX and three other asset classes and a question on participants' correlation forecasting practices.[3] We acknowledge, that extremely short reaction times as measured for the whole Special Questions section are mostly due to reluctance to respond to the non-experimental part of the Special Questions section - correlation assessment. That is why as a robustness check we conduct a separate analysis on the subsample of participants who have filled out all questions from the Special Questions section. Focusing on this subsample of participants who have responded to all Special Questions is also particularly interesting, because these participants are likely to have better statistical knowledge, as indicated by their willingness to provide correlation estimates.

Reaction times are measured in seconds and rescaled in minutes. As the distribution of the reaction time variable is highly negatively skewed we use logarithmized reaction times for the purposes of the subsequent analysis. We run simple OLS regressions with an interaction term between the treatment dummy and log reaction time.

[Insert Table 3 about here]

[Insert Figure 4 about here]

of the framing effect in June 2013 was overall very small and not statistically significant (see Figure 2). Although the reaction times between the waves in March 2013 and June 2013 are not directly comparable, the estimated time participants spent on the experimental question in June 2013 is more than in March 2013. Taken together, the increase of reaction time from March 2013 to June 2013 and at the same time the decrease of the framing effect are in line with hypothesis H3.

[3] The exact wording of the remaining Special Questions is available upon request.

The regression results are displayed in Table 3, columns 1-4. Figure 4 additionally shows the results of a fractional polynomial fit over the forecasts of both treatment groups over reaction time. According to our results the scope of the framing effect decreases with reaction time significantly at the 5% significance level.[4] The results from our reaction time proxy for intuitive thinking are consistent with the results of the self-reported proxies for intuitive thinking - Faith-in-Intuition and Intuitive-Analytical-Score.

3.3 Alternative Explanations

In this section we address the criticism that the framing effect may result from fundamental differences in the information content of the two questions. As already noted in Section 2.2, feedback to a demo version of the questionnaire has indicated that unless stated otherwise participants understand returns as annualized returns instead of monthly percentage change. Although we have explicitly specified that in the questionnaire, it may be argued that some participants overlook the specification and report annualized returns in spite of it. Another potential difference in the information content of the two questions may be connected to the way dividends are treated. In the following we test the general hypothesis that the evidenced framing effect may arise from the participants having a different approach to the calculation of returns or holding different norms regarding the dividend part of the stock market returns. For this purpose we need to consider a group of participants who are likely to have deliberate forecasting strategies and for whom the exact wording of the question is therefore unlikely to lead to different forecasts. Holding the forecasting method constant would allow us to isolate the difference which results from calculating the response in the required response domain (returns or price levels domain) from one's otherwise invariant forecast. An example for such a group of participants is given by the chartists, i.e. participants who heavily rely on technical analysis. Technical analysis provides deliberate technical trading rules based exclusively on historical price levels. When placed in the return group a chartist is unlikely to deviate form technical trading rules but instead he is likely to calculate his return response from his price level forecast.

[4] Unreported regressions with median-centered reaction time instead of logarithmized reaction time show that the framing effect is highly significant at the median reaction time.

In September 2012 we asked participants to assess the importance of several factors for the conduction of their one-month DAX forecasts. An overview of the responses is included in the Appendix (see Figure 6). Among other things we have asked participants on the use of technical analysis. Participants were asked to assess its importance on a Likert-type scale with three categories - ”low”, ”medium” and ”high”. We collected data on the importance of technical analysis for 123 participants in the field experiment. The group sizes are given as follows: high (79 participants), medium (26 participants) and low (18 participants). Table 4 reports the results from panel regressions with interaction terms and cluster-robust standard errors.

[Insert Table 4 about here]

The results indicate that there is no significant framing effect (0.6 percentage points) in the group of chartists. Moving from the group which relies almost exclusively on technical analysis to the group which considers charts of medium importance boosts the framing effect by 3.31 percentage points. The difference in the scope of the framing effect is highly significant at the 1% significance level. We therefore conclude that it is not chartists who drive the framing effect. Furthermore, given that chartists can be assumed to calculate returns according to the same norms as other financial market participants, we can derive from our evidence that differences resulting from the calculation method make up, if any, only an insignificant part of the evidenced framing effect.

It should be noted at this point that the use of deliberate forecasting methods, which satisfy the assumption of procedure invariance, does not mean that this methods are of any value or are rational. It only means that the forecasts are thought through. In this sense not being prone to framing effect is only a necessary but not a sufficient condition for rational expectations.

4 Why Do Professional Forecasters Rely on Their Flawed Intuition?

In the previous section we have shown that reliance on intuition is connected to at least one particular bias in the expectations of professional forecasters - the framing effect. But why would stock market professionals rely on their intuition if it provides flawed responses? What determines whether subjects count on intuition instead of deliberate decision rules (i.e. reasoning) for a particular task in a particular situation at a particular point of time? Dual-processing models differ in the answers they provide to this question. Some dual-processing models assume that the tendency to decide intuitively is a personal trait that is stable over time and over decision situations (see Evans, 2008, for a categorization). We have implicitly adopted this assumption in Section 3.2 when we categorized participants according to the Faith-in-Intuition measure and the Intuitive-Analytical-Score. Another set of models assume that the stronger reliance on intuition depends on exogenous factors such as low motivation and low cognitive capacity. Experimental evidence supports the claim that subjects tend to trust their gut feelings more often when they are unmotivated, cognitively busy or depleted (see e.g., Schoorman, Mayer, Douglas, and Hetrick, 1994; Gilbert, Pelham, and Krull, 1988; Baumeister, Bratslavsky, Muraven, and Tice, 1998). These arguments are relevant in our setting because our participants work in a highly dynamic and stressful environment and we do not provide any monetary incentives for accurate responses. Therefore we formulate and test following hypothesis:

`H4`: *The framing effect is intensified by lack of motivation or lack of cognitive resources.*

A third category of models assumes an internal dialog between both systems. These models assume that intuition (i.e. System 1) provides a fast and effortless assessment in almost all situations and thereby serves as a decision default. Subsequently, reasoning (i.e. System 2) sometimes monitors and eventually corrects the intuitive assessment. The activation of System 2 thereby depends on characteristics of the decision default itself. An example of a more general model in this category is provided by the Parallel-Constraint-Satisfaction (PCS) approach by Glöckner and Betsch (2008a) (discussed by Glöckner, 2008, in light of dual-processing). According to PCS, when making a decision or a forecast based on particular information activated from memory, subjects seek to maximize the fit between the separate pieces of information in their information set. They are particularly fast and confident in their responses when the pieces of information easily fit together, which is typically the case when the activated information set is small. In contrast, subjects become slow, less confident and employ cognitive effort when conflicts (i.e. disagreement) occur, which is likely to be the case in large information sets. The idea that conflicts between the pieces of information result in more cognitive effort is supported by neurobiological evidence (Botvinick, Braver, Barch, Carter, and Cohen, 2001, see e.g.). Simmons and Nelson (2006) provide experimental evidence that the switch from intuitive to analytical responses is determined by intuitive confidence. In the framework of PCS the framing effect may occur when the different questions (price levels vs. returns) activate small and different information sets. The larger the activated information sets, the less different they can be and the lower the expected framing effect. Taken together, PCS predicts a relationship exactly opposite to what can be expected from well-calibrated forecasters, namely, that they will be most confident whenever they are most biased. We formulate following hypothesis to test the implications of PCS for our setting:

`H5`: *Both the framing effect and subjective confidence diminish with reaction time.*

Last but not least, the exact question itself may influence the tendency to suppress intuitive responses. Firstly, (see e.g., Kahneman and Frederick, 2002) suggest that certain formulations can make the applicability of statistical methods more apparent or draw attention to relevant information. Secondly, if the response to a certain question requires information which cannot be activated from memory and a deliberate information search in required, Glöckner and Betsch (2008b) argue that the resulting responses are deliberate, not intuitive.

`H6`: *The tendency to rely on intuition is different for the question on price levels and the question on returns.*

In the following we provide several tests on hypotheses `H4-H6`. In summary, our evidence suggests that the framing effect is driven by the forecasts in the level treatment - fast and evidently flawed responses are more often provided in the level treatment instead of the return treatment. For the level group our results are also in line with the predictions of PCS - fast and flawed responses come with extreme confidence. In contrast, the return group displays a confidence pattern closer to what would be expected from well-calibrated forecasters. We do not find any evidence of a lack of motivation, cognitive busyness or depletion driving the framing effect in our experiment.

4.1 Lack of Motivation

We measure motivation by the relative relevance of the ZEW survey to the other daily activities of the participants. Following Schoorman, Mayer, Douglas, and Hetrick (1994) participants perceive tasks as relevant when their contribution is relevant for the final decision. The absolute relevance of the survey is equal for all participants - the survey forecasts are mainly used for the calculation of sentiment indicators which eventually have an impact on the decisions of others. However, for the group of participants whose daily activity consists of providing forecasts to serve the decisions of others, the relevance of the survey is comparable to their normal activity. In June 2013 we therefore ask participants whether they conduct regular forecasts and if so for which purposes. From 139 respondents 56.8% indicate that they conduct forecasts regularly. Thereof, 50.7% conduct forecasts to serve the decisions of clients and 79.7% report that their forecasts are used for the inhouse trading strategy. We use this group of participants ("Forecasters") as a first proxy for high relative relevance of the ZEW survey. We further approximate the relative relevance of the survey by the participants' occupation assuming that it is lower for active participants such as portfolio managers. Data on the occupation of participants is collected mainly within the scope of Special Questions in March and April 2011. Taken together, hypothesis `H4` a mitigation of the framing effect in the group of Forecasters and an amplification of the bias in the group of portfolio managers.

Table 4, columns 3-6, reports the results for both proxies. We estimate coefficients from panel regressions with cluster-robust standard errors. The results indicate a significant framing effect (1.64 percentage points, significant at the 1% level) in the group of Forecasters. Against the prediction of hypothesis `H4`, the framing effect is even lower by 0.57

percentage points in the group of participants who do not conduct forecasts outside the scope of the ZEW survey, although the difference is not statistically significant at the 10% significance level. The results on our second proxy - occupation as a portfolio manager - also do not support `H4`. The framing effect in the group of portfolio managers is 0.77 percentage points and statistically insignificant.

4.2 Cognitive Busyness

We approximate cognitive busyness and depletion by the exact timing of the submission of the response. We hypothesize that the framing effect should be intensified on Fridays driven by distraction from the upcoming weekend (as evidenced by DellaVigna and Pollet, 2009). The exact timing of the response is an appropriate measure of cognitive busyness because it is largely exogenously determined by the timing of emails and reminders by the ZEW team to the participants. We argue that this is the case for the following reasons: Firstly, the majority of 70.55% of the responses are submitted on a Monday or a Friday as illustrated in the Appendix, Figure 8, which can be explained by scheduled beginning and end of the survey waves on Mondays and scheduled reminders on Fridays. Secondly, there is a clustering of responses in the morning (52.6% of the responses are submitted before 12 o'clock), especially on Mondays and Fridays, which can be explained by the fact that any emails to the participants are sent out before noon. Nevertheless, we acknowledge that our results may underestimate the impact of cognitive busyness. In situations of extreme cognitive overload, participants are unlikely to begin the survey. Hence, our results rather reflect the impact of different variations of moderate cognitive busyness on the framing effect.

[INSERT TABLE 5 ABOUT HERE]

Table 5, columns 1-2, displays the regression results from panel regressions with cluster-robust standard errors. Against the predictions of `H4`, the framing effect does not increase, but rather decreases by 0.84 percentage points for responses submitted on a Friday. The decrease is statistically significant at the 10% significance level for one of the specifications ("daily avg").

We further focus on fluctuations in the scope of the framing effect during the day. In line with Gilbert, Pelham, and Krull (1988) reliance on intuition intensifies in times when people are cognitively busy, meaning that they have to perform a lot of tasks either simultaneously or consecutively. For financial market professionals this is particularly the case when the activity on the markets is high. Hence, we hypothesize that participants are more cognitively busy at the beginning and the end of the trading session when the trading volume on stock markets is usually higher (see e.g., Admati and Pfleiderer, 1988, for a theoretical explanation on this intraday volume pattern). This would imply a U-shaped development of the framing effect over the day. An alternative hypothesis can be derived in line with Baumeister, Bratslavsky, Muraven, and Tice (1998), namely that participants are cognitively depleted at the end of the trading session and are more likely to rely on their intuition. This would imply that the framing effect should be small at the beginning of the trading day and should increase until its end. We test both aforementioned hypotheses by estimating panel regressions with cluster-robust standard errors as displayed in Table 5. Included are only responses which were submitted during the trading session. Table 5, columns 3-6 show that the framing effect does not change significantly over the trading session, neither economically nor statistically.

4.3 Intuitive Confidence

We have already shown in Section 3.2 that the framing effect prevails in fast responses. In the following we test whether the fast and biased responses are also connected to extreme confidence as stated in `H6` or whether the subjective confidence develops according to what would be expected from well-calibrated forecasters. The results from OLS regressions of the width of subjective confidence intervals on reaction time based on the sample in March 2013 are displayed in Table 3, columns 5-8. The coefficient β_2 describes the development of the interval width of the level group with reaction time. The positive coefficients indicate that the subjective confidence decreases the more time the participants take to respond. The decrease is even statistically significant at the 5% significance level for the specifications in columns 6 and 8. The results for the level group are therefore in line with the predictions of PCS - fast and flawed forecasts are provided with high confidence.

The confidence of the return group, however, develops in the opposite direction. The results of analogous regressions with a dummy for the level group, instead of the return group are included in the Appendix, Table 7. Against the predictions of `H6`, the confidence interval of the return group becomes narrower with reaction time, although the difference is not statistically significant. The return group therefore provides at least some indication of an ongoing calibration process, although not statistically significant, of the confidence intervals in contrast to the level group.

4.4 The Domain of Price Levels

In the background of the asymmetry between return group and the level group documented in the previous section, it should be noted that there is also an apparent asymmetry in the development of the forecasts of both groups over time. Table 3 reveals that the evidenced decrease of the framing effect with reaction time is due to significant change in the level forecasts with reaction time, not the return forecasts. This indicates that it is the fast and flawed forecasts of the level group, not the return group, that drive the framing effect. Together with the observation that the fast and flawed forecasts of the level group are provided with high confidence, this gives rise to the hypothesis that return forecasts are generally more thought through and level forecasts are on average more intuitive. A comparison of the mean reaction time of both groups provides support for this claim. It takes on average additional 1.57 minutes to respond to the return question, a difference which is significant at a 10% significance level according to a non-parametric Mann-Whitney test. For the subsample of participants who have responded to the whole Special Questions section this difference is on average 10.2 seconds and not significant at the 10% significance level.[5]

[5] Similar results are obtained from a Wald-test on the log reaction times.

The evidenced tendency to forecast more deliberately in the return treatment as opposed to the level treatment is in line with the hypothesis that some formulations, in this case the return formulation, make the applicability of more time-consuming statistical methods more apparent (see Kahneman and Frederick, 2002). It is also in line with the hypothesis, that the return formulation requires information that participants cannot recall and therefore have to search deliberately (see Glöckner and Betsch, 2008b), namely information on past returns. Andreassen (1988) makes a strong case for this hypothesis by providing experimental evidence that price charts are easier to recall than return charts. Even if both charts are available, subjects appear to pay more attention to the price level charts. Prior to the beginning of the field experiment, in December 2011, we asked professionals which numbers they consider when they gather information about the stock market indices they regularly track. Among the responses we included the responses ”index level” and ”index return”.[6] We collected data from 142 participants. Only a minority of 16.9% participants indicated that they inform themselves of the index return. Most of them do so in addition to getting informed about the current index level and only 2 participants inform themselves only on the index returns. The evidence that participants do not pay attention on stock returns in the first place, makes a strong case for the hypothesis that they cannot recall relevant information when they are asked to forecast returns (e.g. historical average monthly return) but rather have to search for it deliberately, which in turn induces a deliberate forecasting strategy.

Before the beginning of the experiment, in March 2012 we also examined participants' preferences towards price levels as a response domain. We asked participants on their short-term DAX forecasts and thereby allowed them to provide either a return forecast or a price level forecast. From 136 professionals who submitted a response only 4.41% submitted a return forecast, which indicates a strong preference towards responding in the price levels domain. The evidence raises another concern, which highlights the relevance of research on judgmental forecasting for real-world situations - participants are most biased in the domain they are most comfortable with and are likely to use at most.

[6] Other response categories were given as follows: high-low spread, historical volatility, implied volatility, trading volume.

5 Conclusions

Our experiment so far allows conclusions on at least one channel through which the framing effect influences the development of financial markets, that is through the recommendations of analysts who as a group are particularly prone to the judgmental bias. Womack (1996) and Barber, Lehavy, McNichols, and Trueman (2001) provide evidence that the forecasts of analysts are indeed relevant for the decisions of traders and have a significant influence on the development of the market price. Given that these forecasts are influenced by a superficial aspect such as the domain in which they are conducted, it can well be the case that incorporating them actually decreases instead of increases the information efficiency of the market price. Further analysis of this issue is particularly relevant in light of our evidence that professionals are rather homogeneous in their preferences upon one particular forecast domain, hence the impact of the framing effect cannot be averaged out by considering analysts' forecasts in the aggregate. Moreover, it is exactly the more strongly preferred price levels domain, which makes professionals more prone to providing fast, confident but flawed responses, which highlights the real-world relevance of research on judgmental forecasting in general.

Table 1: Framing Effect: Evidence, Statistical Knowledge and Experience

Table 1 reports regression coefficients for the framing effect in DAX one-month forecasts. Level forecasts are converted into return forecasts by means of DAX daily open on the day of the response (calculation method "daily open") or by means of DAX daily average on the day of the response (calculation method "daily avg"). Daily data on DAX is downloaded from Datastream. Reported are coefficients from panel regressions with cluster-robust standard errors. The independent variables are given and coded as follows: return group dummy (D^{ret}= 1 if return group); statistical knowledge approximated by self-reported importance of econometric models for one's own one-month and six-month DAX forecasts ($D^{stat-low}$= 1 if econometric models have low importance for short-term and mid-term forecasts, $D^{stat-med}$= 1 if econometric models have at least medium importance for short-term or mid-term forecasts, $D^{stat-med}$= 0 and $D^{stat-low}$= 0 if econometric models have high importance for either short-term or mid-term forecasts); experience approximated by experience with one-month DAX forecasts based on the responses to one's usual forecasting horizon of DAX forecasts (D^{noexp}= 0 if response category "<1 month" or "1-3 months").

$$
\begin{aligned}
r_{it} &= \beta_0 + \beta_1 D^{ret} + \beta_2 D^{lt} + \beta_3 D^{ret} D^{lt} + u_i + \epsilon_{it} \\
r_{it} &= \beta_0 + \beta_1 D^{ret} + \beta_2 D^{stat-med} + \beta_3 D^{stat-low} + \beta_4 D^{ret} D^{stat-med} \\
&\quad + \beta_5 D^{ret} D^{stat-low} + u_i + \epsilon_{it}
\end{aligned}
$$

	(1)	(2)	(3)	(4)	(5)	(6)
calc. method	daily open	daily avg	daily open	daily avg	daily open	daily avg
D^{ret}	0.0135***	0.0144***	0.0218***	0.0223***	0.0076	0.0083
	(0.0038)	(0.0038)	(0.0078)	(0.0077)	(0.0091)	(0.0092)
D^{noexp}			0.0103*	0.0102*		
			(0.0061)	(0.0060)		
$D^{ret}D^{noexp}$			-0.0086	-0.0084		
			(0.0093)	(0.0093)		
$D^{stat-med}$					-0.0026	-0.0026
					(0.0065)	(0.0067)
$D^{stat-low}$					-0.0102	-0.0101
					(0.0063)	(0.0064)
$D^{ret}D^{stat-med}$					0.0017	0.0017
					(0.0118)	(0.0118)
$D^{ret}D^{stat-low}$					0.0124	0.0123
					(0.0114)	(0.0115)
_cons	-0.0002	-0.0011	-0.0095*	-0.0100*	0.0070	0.0063
	(0.0023)	(0.0023)	(0.0054)	(0.0053)	(0.0047)	(0.0048)
N	535	535	413	413	392	392
N_g	188	188	134	134	122	122

Clustered standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Table 2: Framing Effect and Self-Reported Level of Intuitive Forecasting

Table 2 reports regression coefficients for intergroup differences in the scope of the framing effect in DAX one-month forecasts. Level forecasts are converted into return forecasts by means of DAX daily open on the day of the response (calculation method "daily open") or by means of DAX daily average on the day of the response (calculation method "daily avg"). Daily data on DAX is downloaded from Datastream. Reported are coefficients from panel regressions with cluster-robust standard errors. In columns (1)-(4) intuition refers to Faith-in-Intuition as measured by self-reported importance of intuition for the conduction of short-term (1 month ahead) stock market forecasts - "low", "medium" or "high". In columns (5)-(8) intuition refers the Intuitive-Analytical Score - relative importance of intuition as compared to the importance of the most important among the analytical methods (for a list of all analytical methods see Appendix, Table 6). The independent variables are given and coded as follows: return group dummy (D^{ret}= 1 if return group); intuition approximated by Faith-in-Intuition and Intuitive-Analytical-Score respectively (D^{i2}= 1 if middle category of intuitive thinking, D^{i1}= 1 if lowest category of intuitive thinkng, D^{i2}=0 and D^{i1}=0 if highest category of intuitive thinking).

$$r_{it} = \beta_0 + \beta_1 D^{ret} + \beta_2 D^{i2} + \beta_3 D^{i1} + \beta_4 D^{ret} D^{i2} + \beta_5 D^{ret} D^{i1} + u_i + \epsilon_{it}$$

	(1)	(2)	(3)	(4)
calc. intuition	daily open absolute	daily avg absolute	daily open relative	daily avg relative
$\beta_1 = r^{ret,i3}$	0.0206**	0.0216**	0.0255***	0.0260***
	(0.0090)	(0.0091)	(0.0074)	(0.0074)
$\beta_2 = r^{lev,i2} - r^{lev,i3}$	0.0026	0.0031	0.0073	0.0072
	(0.0067)	(0.0068)	(0.0063)	(0.0064)
$\beta_3 = r^{lev,i1} - r^{lev,i3}$	0.0070	0.0067	0.0105	0.0097
	(0.0075)	(0.0076)	(0.0074)	(0.0075)
$\beta_4 = (r^{ret,i2} - r^{lev,i2}) - (r^{ret,i3} - r^{lev,i3})$	-0.0090	-0.0094	-0.0183*	-0.0181*
	(0.0111)	(0.0112)	(0.0099)	(0.0100)
$\beta_5 = (r^{ret,i1} - r^{lev,i1}) - (r^{ret,i3} - r^{lev,i3})$	-0.0115	-0.0111	-0.0192	-0.0184
	(0.0120)	(0.0121)	(0.0118)	(0.0118)
$\beta_0 = r^{lev,i3}$	-0.0019	-0.0029	-0.0043	-0.0048
	(0.0055)	(0.0056)	(0.0051)	(0.0052)
N	396	396	395	395
N_g	123	123	122	122

Clustered standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Table 3: Development of Framing Effect and Level Forecasts with Reaction Time

Table 3 reports regression coefficients for the development of the framing effect in DAX one-month forecasts and subjective 90% confidence intervals on the DAX one-month forecasts with reaction time in the subsample of March 2013. Level forecasts are converted into return forecasts by means of actual DAX daily open on the day of the response (calculation method "daily open") and daily average on the day of the response (calculation method "daily avg"). DAX daily data is downloaded from Datastream. Columns (1), (3), (5) and (7) report the results for regressions on the whole sample and columns (2), (4), (6) and (8) report the results on the participants who have filled in the entire Special Questions section (group with sound statistical knowledge). The reaction time T^*_{ij} is measured in second, rescaled in minutes and logarithmized.

$$r_i = \beta_0 + \beta_1 D^{ret} + (\beta_2 + \beta_3 D^{ret})T^*_i + \epsilon_i$$
$$CI(90\%)_i = \beta_0 + \beta_1 D^{ret} + (\beta_2 + \beta_3 D^{ret})T^*_i + \epsilon_i$$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Expectations on DAX 1m [percentage points]				90% Confidence Interval on DAX 1m			
	daily open	daily open	daily avg	daily avg	daily open	daily open	daily avg	daily avg
β_1	0.0209***	0.0494***	0.0219***	0.0492***	0.0139	0.102	0.0140	0.102
	(0.0068)	(0.0134)	(0.0068)	(0.0134)	(0.0268)	(0.0689)	(0.0267)	(0.0689)
β_2	0.00942**	0.0259***	0.00893**	0.0245***	0.0178	0.0727**	0.0178	0.0726**
	(0.0037)	(0.0071)	(0.0037)	(0.0071)	(0.0139)	(0.0365)	(0.0139)	(0.0365)
β_3	-0.0120**	-0.0284***	-0.0115**	-0.0270***	-0.0368*	-0.1000**	-0.0367*	-0.0999**
	(0.0052)	(0.0087)	(0.0052)	(0.0087)	(0.0199)	(0.0447)	(0.0199)	(0.0446)
β_0	-0.0019	-0.0257**	-0.0029	-0.0255**	0.0796***	0.00737	0.0795***	0.0073
	(0.0043)	(0.0104)	(0.0043)	(0.0103)	(0.0162)	(0.0531)	(0.0161)	(0.0531)
N	118	46	118	46	111	46	111	46

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Table 4: Framing Effect and Deliberate Forecasting Strategies

Table 4 reports regression coefficients for intergroup differences in the framing effect in DAX one-month forecasts. Level forecasts are converted into return forecasts by means of DAX daily open on the day of the response (calculation method ”daily open”) and daily average on the day of the response (calculation method ”daily avg”) . Daily data on DAX is downloaded from Datastream. Reported are coefficients from panel regressions with cluster-robust standard errors. The independent variables are given and coded as follows: return group dummy (D^{ret}= 1 if return group); technical analysis refers to self-reported importance of technical analysis for the conduction of one-month DAX forecasts (D^{ta2}= 1 if medium importance, D^{ta1}= 1 if low importance, D^{ta2}=0 and D^{ta1}=0 if high importance of technical analysis); occupation as a portfolio manager (D^{noPfM}=1 if participant is not a portfolio manager); a proxy for occupation as a professional forecaster ($D^{noFcster}$=1 if participant does not conduct on a regular basis forecasts outside the scope of the ZEW Financial Market Survey).

$$
\begin{aligned}
r_{it} =& \beta_0 + \beta_1 D^{ret} + \beta_2 D^{ta2} + \beta_3 D^{ta1} + \beta_4 D^{ret} D^{ta2} + \beta_5 D^{ret} D^{ta1} + u_i + \epsilon_{it} \\
r_{it} =& \beta_0 + \beta_1 D^{ret} + \beta_2 D^{k} + \beta_3 D^{ret} D^{k} + +u_{0i} + \epsilon_{it}(+u_{1i} D^{ret} + \gamma_t) \ ,k\epsilon\{noPfM, noFcster\}
\end{aligned}
$$

	(1)	(2)		(3)	(4)	(5)	(6)
	daily open	daily avg		daily open	daily avg	daily open	daily avg
D^{ret}	0.00616	0.00698	D^{ret}	0.00766	0.00863	0.0164***	0.0171***
	(0.00573)	(0.00575)		(0.0110)	(0.0111)	(0.00470)	(0.00471)
D^{ta2}	-0.0124*	-0.0122*	D^{noPfM}	0.000777	0.00101		
	(0.00643)	(0.00650)		(0.00652)	(0.00665)		
D^{ta1}	-0.00121	-0.00116	$D^{noFcster}$			0.00173	0.00186
	(0.00603)	(0.00613)				(0.00523)	(0.00526)
$D^{ret}D^{ta2}$	0.0331***	0.0329***	$D^{ret}D^{noPfM}$	0.00625	0.00599		
	(0.00916)	(0.00921)		(0.0118)	(0.0118)		
$D^{ret}D^{ta1}$	0.00340	0.00337	$D^{ret}D^{noFcster}$			-0.00570	-0.00583
	(0.0114)	(0.0115)				(0.00829)	(0.00830)
_cons	0.00401	0.00318		-0.00210	-0.00306	-0.00187	-0.00253
	(0.00379)	(0.00382)		(0.00592)	(0.00608)	(0.00329)	(0.00330)
N	396	396		484	484	449	449
N_g	123	123		167	167	139	139

Clustered standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Table 5: Impact of Cognitive Busyness on Framing Effect

Table 5 reports regression coefficients for the development of the framing effect in DAX one-month forecasts with cognitive busyness or depletion. Level forecasts are converted into return forecasts by means of actual DAX daily open on the day of the response (calculation method "daily open") and daily average on the day of the response (calculation method "daily avg"). DAX daily data is downloaded from Datastream. Reported are coefficients from panel regressions with cluster-robust standard errors. The independent variables are given and coded as follows: return group dummy (D^{ret}= 1 if return group); cognitive busyness approximated by day of the week (D^{Fri}= 1 if response submitted on a Friday); cognitive busyness approximated by the hours of the day (H time of the submission is measured in hours and centered around 13 o'clock).

$$r_{it} = \beta_0 + \beta_1 D^{ret} + \beta_2 D^{Fri} + \beta_3 D^{ret} D^{Fri} + u_i + \epsilon_{it}$$
$$r_{it} = \beta_0 + \beta_1 D^{ret} + (\beta_2 + \beta_3 D^{ret}) H_{it} + (\beta_4 + \beta_5 D^{ret}) H_{it}^2 + u_i + \epsilon_{it}$$

	(1)	(2)		(3)	(4)	(5)	(6)
	daily open day of week	daily avg day of week		daily open time of day	daily avg time of day	daily open time of day	daily avg time of day
D^{ret}	0.0161***	0.0177***	D^{ret}	0.0125***	0.0134***	0.0127***	0.0135***
	(0.00412)	(0.00411)		(0.00382)	(0.00382)	(0.00457)	(0.00458)
D^{Fri}	0.00514	0.00760*	H_{it}	0.000886	0.000898	0.000792	0.000792
	(0.00462)	(0.00458)		(0.000625)	(0.000640)	(0.000600)	(0.000615)
$D^{ret}D^{Fri}$	-0.00837	-0.0108*	$D^{ret}H_{it}$	-0.000706	-0.000717	-0.000739	-0.000737
	(0.00638)	(0.00635)		(0.00104)	(0.00105)	(0.00111)	(0.00112)
			H_{it}^2			-0.0000922	-0.000105
						(0.000227)	(0.000236)
			$D^{ret}H_{it}^2$			-0.0000500	-0.0000366
						(0.000397)	(0.000402)
_cons	-0.00176	-0.00334	_cons	0.000948	0.0000767	0.00160	0.000825
	(0.00260)	(0.00260)		(0.00233)	(0.00233)	(0.00285)	(0.00287)
N	535	535		514	514	514	514
N_g	188	188		188	188	188	188

Clustered standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Figure 1: Market Phases Covered by the Field Experiment

Daily data on DAX Performance index as well as Gold price (LME spot, in USD) were taken from Datastream. The reference lines correspond to the respective timing of the waves in September 2012, December 2012, March 2013 and June 2013. Gold forecasts were included since March 2013.

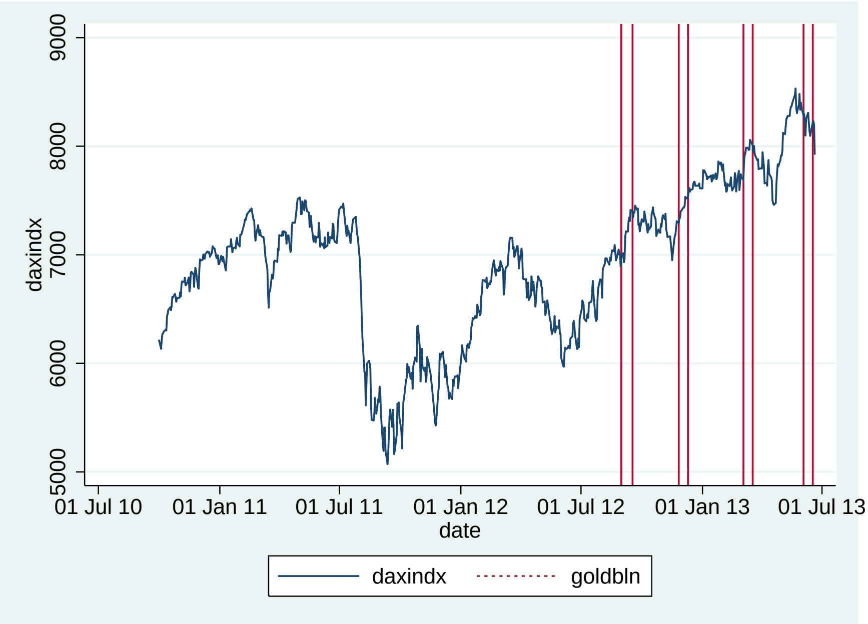


Figure 2: Difference between Return Forecasts and Index Level Forecasts

Figure 2 displays the cumulative distributions of the return forecasts by the return group and the level group, respectively. Return forecasts of the level group are calculated from level forecasts and DAX daily open on the day of the response.

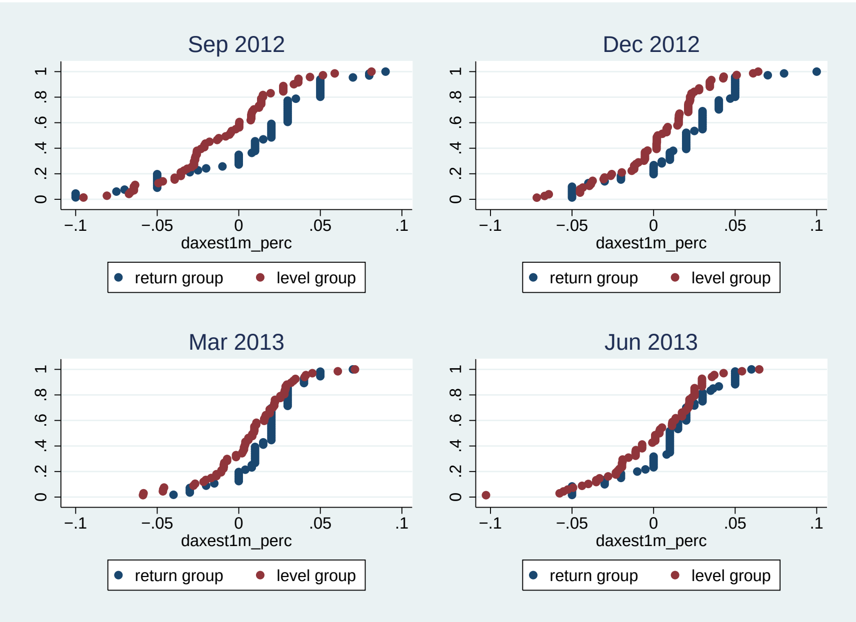


Figure 3: Impact of Intuitive Thinking on Framing Effect

Figure 3 displays differences in the scope of the framing effect depending on self-reported level of intuitive thinking. The left graph displays regression results for intuitive thinking as approximated by "Faith in Intuition" (*absolute importance of intuition*). The right graph displays regression results for intuitive thinking as approximated by the "Intuitive-Analytical Score" (*relative importance of intuition*). The corresponding regressions are displayed on Table 2.

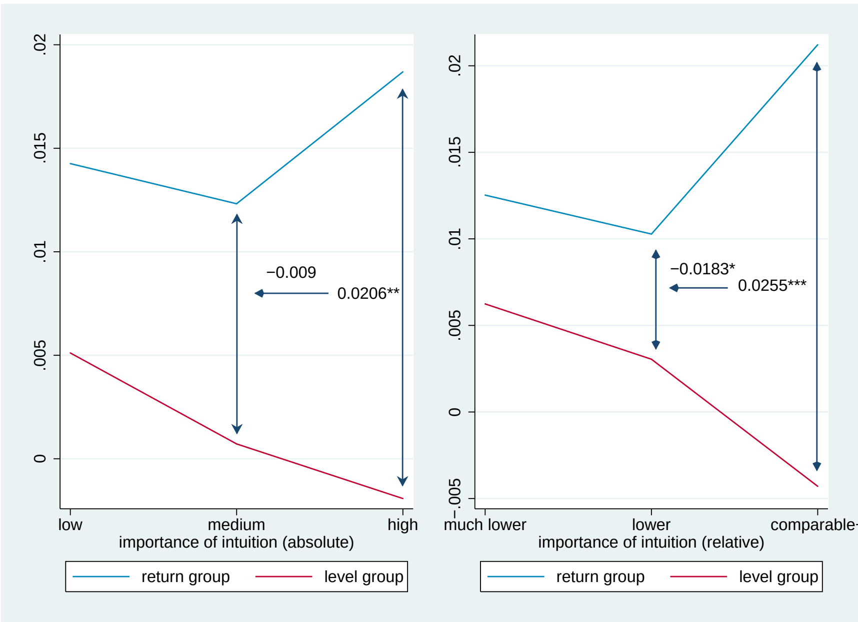


Figure 4: Impact of Reaction Time on Framing Effect

Figure 4 displays forecasts of the return group and the level group depending on the reaction time. Fractional polynomials are used for the predicted lines. The left part contains all responses, the right part displays the results only for the participants who have responded to the whole Special Questions section (participants with sound statistical knowledge). Vertical reference lines indicate respective median reaction times. For the calculation of return forecasts of the level group DAX daily open on the day of the response is applied.

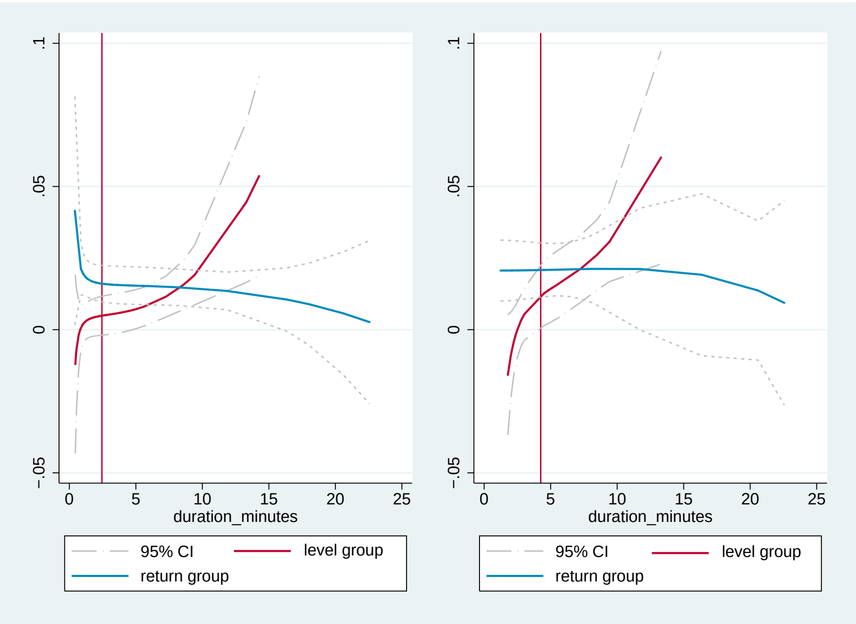
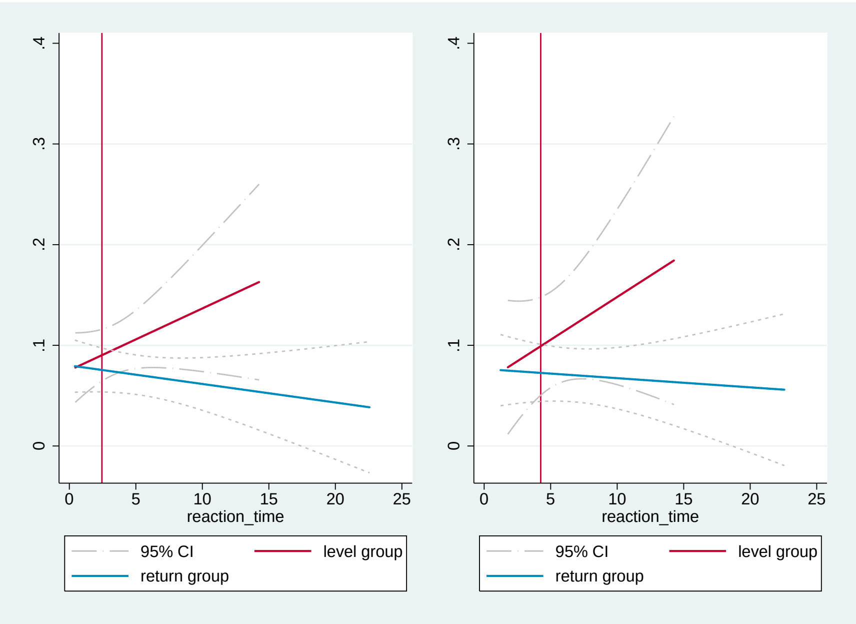


Figure 5: Link between Reaction Time and Confidence

Figure 5 displays the width of the subjective confidence intervals (in percent) of the return group and the level group depending on the reaction time (linear fit). The left part contains all responses, the right part displays the results only for the participants who have responded to the whole Special Questions section (participants with sound statistical knowledge). Vertical reference lines indicate respective median reaction times. For the calculation of return forecasts of the level group DAX daily open on the day of the response is applied.



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6 Appendix

Table 6: Variable Definitions

Variable	Description
TREATMENT GROUPS	
- Description:	Return and level treatment, randomized, between-subject design
- Question wording:	[return treatment] *Within 1 month I expect a DAX return (monthly percentage change) of ...%*
	With a probability of 90% the DAX return will then lie between ...% and ...%
	[level treatment] *I expect the DAX in 1 month at ... points.*
	With a probability of 90% the DAX will then lie between ... and ... points.
- Timing:	Sep 2012-Jun 2013 for DAX; Mar 2013-Jun 2013 for gold price
- Coding:	$D^{ret} = 1$ & $D^{lev} = 0$ for return treatment
	$D^{ret} = 0$ & $D^{lev} = 1$ for level treatment
IMPORTANCE OF DIVERSE METHODS	
- Description:	Self-reported importance of diverse methods for the conduction of own forecasts (short-term forecasts and mid-term forecasts are elicited separately);
- Time of elicitation:	Special Question in September 2012
- Question wording:	*How important are following factors for your [e.g., short-term (1 month ahead)] DAX forecasts?*
	... technical analysis, fundamental analysis, econometric models, intuition, experience, consensus forecasts, inhouse forecasts, simulations
- Response categories:	"low", "medium", "high"
- Coding:	e.g., $D^{ta1} = 1$ if importance of technical analysis (TA) is "low"
	$D^{ta2} = 1$ if importance of TA is "medium"
	$D^{ta2} = 0$ & $D^{ta1} = 0$ if importance of TA is "high"
STATISTICAL KNOWLEDGE	
- Description:	Composite measure of self-reported importance of econometric models (EM) for own forecasts (short-term and mid-term)
- Time of elicitation:	Special Question in September 2012
- Question wording:	*How important are following factors for your [short-term (1 month ahead) / mid-term (6 months ahead)] DAX forecasts?*

Continued on next page

Table 6 – continued from previous page

Variable	Description
	... econometric models
- Response categories:	"low", "medium", "high" (for short-term and mid-term forecasts respectively)
- Coding:	$D^{stat-low} = 1$ if "low" importance of EM for both short-term and mid-term forecasts
	$D^{stat-med} = 1$ if "medium" importance of EM for either short-term or mid-term forecasts
	$D^{stat-med} = 0$ & $D^{stat-low} = 0$ if "high" importance of EM for either short-term or mid-term forecasts
Experience	
- Description:	Approximated by matching usual forecasting horizon and the forecast horizon in the experiment (1 mth). Self-reported data on the usual forecast/investment horizon
- Time of elicitation:	Special Question in March 2012
- Question wording:	*What is the usual forecasting horizon of your DAX forecasts? (1 month ahead) / mid-term (6 months ahead)] DAX forecasts?*
	... econometric models
- Response categories:	"< 1mth", "1-3 mths", "3-6 mths", "6-12 mths","> 1y"
- Coding:	$D^{lt} = 0$ for "<1mth" or "1-3 mths"
	$D^{lt} = 1$ otherwise
Occupation	
A. Portfolio manager	
- Description:	Self-reported occupation
- Time of elicitation:	Special Question in March/April 2011 merged with data from registration form of subjects who entered the panel after 2010
- Coding:	$D^{PfM} = 1$ for occupation "Portfolio Manager"
	$D^{PfM} = 0$ otherwise
B. Forecaster	
- Description:	Self-reported information on regularly conducted forecasts outside the scope of the ZEW Financial Market Survey
- Time of elicitation:	Special Question in March 2013
- Question wording:	*What is the usual type of your regular forecasts outside the scope of the ZEW Financial Market Survey?*
- Response categories:	"level forecasts", "return forecasts", "range forecast" "directional forecast", "probability estimate", "other"

Continued on next page

Table 6 – continued from previous page

Variable	Description
	"I do not conduct any explicit forecast"
- Coding:	$D^{noFcster} = 1$ if does not conduct any explicit forecasts outside the scope of the ZEW Financial Market Survey $D^{noFcster} = 0$ if participant conducts forecasts on a regular basis
INTUITIVE FORECASTING	
A. FAITH IN INTUITION	
- Description:	Self-reported importance of intuition for the conduction of own short-term DAX forecast
- Time of elicitation:	Special Question in September 2012
- Question wording:	*How important are following factors for your [short-term (1 month ahead)] DAX forecasts?* *... intuition*
- Response categories:	"low", "medium", "high"
- Coding:	$D^{i1} = 1$ if importance of intuition is "low" $D^{i2} = 1$ if importance of intuition is "medium" $D^{i2} = 0$ & $D^{i1} = 0$ if importance of intuition is "high"
B. INTUITIVE-ANALYTICAL SCORE	
- Description:	Self-reported importance of intuition for the conduction of own short-term DAX forecast compared to the self-reported importance of the most important analytical method; Analytical methods: technical and fundamental analysis, econometric tools, simulations, inhouse and consensus forecasts
- Time of elicitation:	Special Question in September 2012
- Coding:	$D^{i1} = 1$ if intuition is much less (by 2 categories) important than analytical methods $D^{i2} = 1$ if intuition is less (by 1 category) important than analytical methods $D^{i2} = 0$ & $D^{i1} = 0$ if intuition is of comparable or higher importance
C. REACTION TIME	
- Description:	The time between the beginning of the Special Questions section and the submission of the questionnaire is measured in seconds and converted into minutes. The

Continued on next page

Table 6 – continued from previous page

Variable	Description
	Special Questions section in March 2013 contains questions on DAX and gold price forecasts, correlation assessments between DAX and other asset classes and a comments field; Excluded are participants who submitted a comment and participants who returned to the main questionnaire after entering the Special Questions section
- Time of elicitation:	March 2013
- Variable definition:	T_{ij} is the median-centered reaction time (in minutes); for different subsamples the respective sample median applies
Cognitive Busyness	
A. Day of Week	
- Description:	Cognitive busyness is approximated by the timing of the response (day of week); Response timing is measured by the time of the submission of the questionnaire
- Time of elicitation:	every wave
- Variable definition:	$D^{Fri} = 1$ if the questionnaire is submitted on a Friday
B. Hour of Day	
- Description:	Cognitive busyness is approximated by the timing of the response (hour of day); Hour of day refers to the time of the submission of the questionnaire
- Time of elicitation:	every wave
- Variable definition:	H_{it} is the hour of the submission centered around 1 p.m.

Table 7: Development of Framing Effect and Return Forecasts with Log Reaction Time

Table 7 reports regression coefficients for the development of the framing effect in DAX one-month forecasts and subjective 90% confidence intervals on the DAX one-month forecasts with reaction time in the subsample of March 2013. Level forecasts are converted into return forecasts by means of actual DAX daily open on the day of the response (calculation method "daily open") and daily average on the day of the response (calculation method "daily avg"). DAX daily data is downloaded from Datastream. Columns (1), (3), (5) and (7) report the results for regressions on the whole sample and columns (2), (4), (6) and (8) report the results on the participants who have filled in the entire Special Questions section (group with sound statistical knowledge). The reaction time T^*_{ij} is measured in second, rescaled in minutes and logarithmized.

$$r_{ij} = \beta_0 + \beta_1 D^{lev} + (\beta_2 + \beta_3 D^{lev}) ln(T_{ij}) + \gamma_j + \epsilon_{ij}$$
$$CI(90\%)_{ij} = \beta_0 + \beta_1 D^{lev} + (\beta_2 + \beta_3 D^{lev}) ln(T_{ij}) + \gamma_j + \epsilon_{ij}$$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Expectations on DAX 1m [percentage points]				90% Confidence Interval on DAX 1m			
	daily open	daily open	daily avg	daily avg	daily open	daily open	daily avg	daily avg
β_1	-0.0209***	-0.0494***	-0.0219***	-0.0492***	-0.0139	-0.102	-0.0140	-0.102
	(0.0068)	(0.0134)	(0.0068)	(0.0134)	(0.0268)	(0.0689)	(0.0267)	(0.0689)
β_2	-0.0026	-0.0025	-0.0026	-0.0025	-0.0189	-0.0272	-0.0189	-0.0272
	(0.0037)	(0.0050)	(0.0036)	(0.0050)	(0.0142)	(0.0257)	(0.0142)	(0.0257)
β_3	0.0120**	0.0284***	0.0115**	0.0270***	0.0368*	0.1000**	0.0367*	0.0999**
	(0.0052)	(0.0087)	(0.0052)	(0.0087)	(0.0199)	(0.0447)	(0.0199)	(0.0446)
β_0	0.0189***	0.0237***	0.0189***	0.0237***	0.0935***	0.109**	0.0935***	0.109**
	(0.0053)	(0.0086)	(0.0053)	(0.0085)	(0.0213)	(0.0439)	(0.0213)	(0.0439)
N	118	46	118	46	111	46	111	46

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Figure 6: Methods Used for Short-Term DAX Forecasts

Displayed is the number of respondents who have indicated that a particular method has a high, medium or low importance for the conduction of their DAX forecasts 1 month ahead.

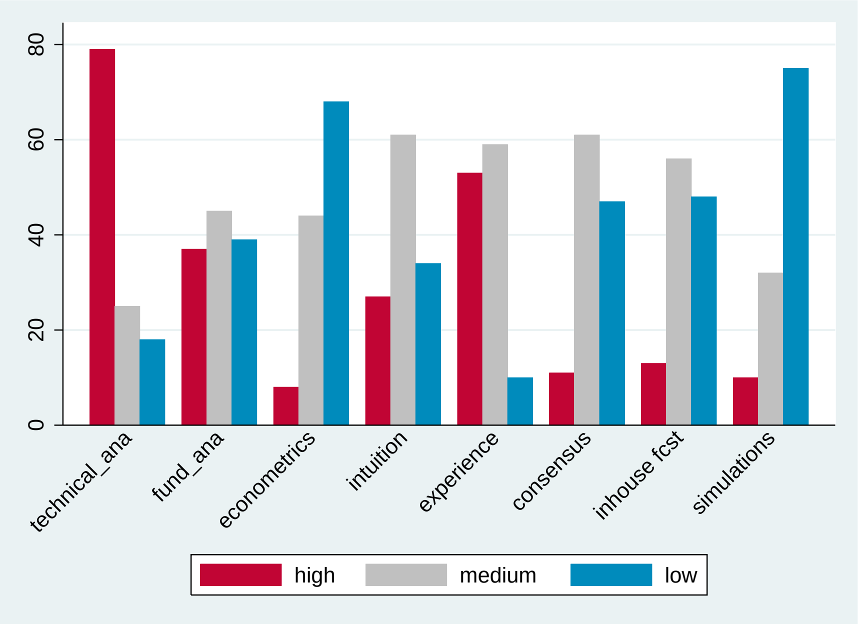

Figure 7: Usual Forecast/Investment Horizon and Preferences towards Response Mode

Displayed is the sample distribution of usual forecast/investment horizons among the participants (left graph). Participants' preferences towards a particular response mode were elicited in March 2012.

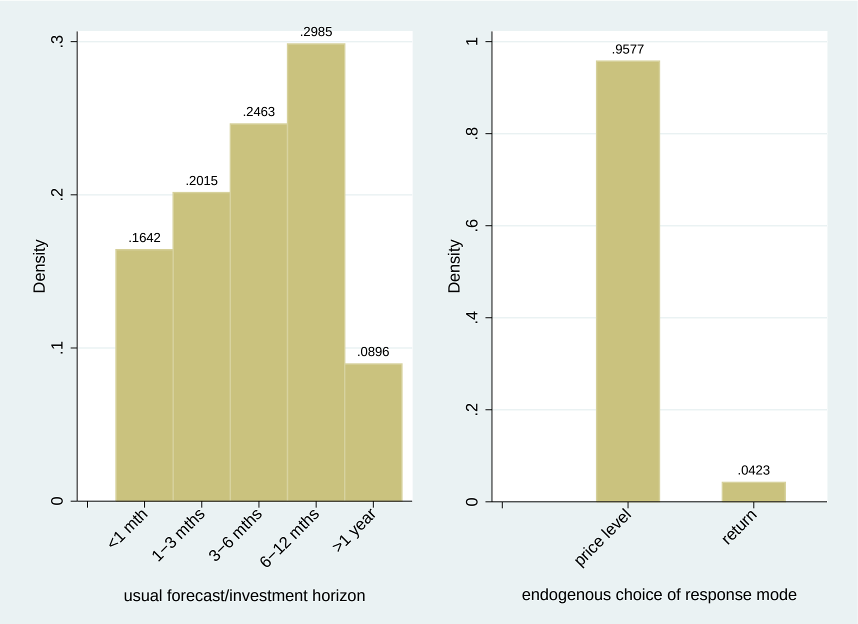

Figure 8: Response Timing